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Fast Content Based Image Retrieval Using Zernike Moments

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Abstract

Content Based Image Retrieval (CBIR) is an important research area for manipulating large amount of image databases and archives. In a broad sense, features include visual features like color, texture, shape etc. In order to extract features of an image, various feature extraction methods are available. One of them is moment description. The Zernike Moment Descriptor is a moment based Shape Descriptor. It has many desirable properties such as rotation invariance, robustness to noise, expression efficiency and fast computation for describing the shapes of patterns. In this paper, we perform fast Content Based Image Retrieval (CBIR) of images from a database for the given query image. We have shown how fast computation of radial polynomials for computing Zernike Moments (ZMs) leads to the fast retrieval of relevant images according to the similarity measure calculated between features of the query image and images of the image database.

Keywords: *Content Based Image Retrieval; Zernike Moments; Fast Computation.*

1. Introduction

An image retrieval system is a computer system for browsing, searching and retrieving images in an image database. Text based and content based are the two techniques for search and retrieval in image database. Text based retrieval is non-standardized because different users use different keywords. Text descriptions are sometimes subjective and incomplete because it cannot depict complicated image features very well. Content based image retrieval (CBIR) technique use image content to search and retrieve images. Content based image retrieval system was introduced to address the problems associated with text-based image retrieval. It is based on extracting and comparing the visual attributes of the images. Examples of visual attributes are color, texture, shape, and motion parameters. The users usually formulate query image and present to the system. The system extracts the visual attributes of the query image in the same mode as it does for each database image, and then identifies images in the database whose feature vectors match those of the query image, and sorts the best similar objects according to their similarity measure.

An elective shape descriptor is a key component of multimedia content description, since shape is a fundamental property of an object. There are two types of shape descriptors: contour based shape descriptors and region based shape descriptors [1]. Contour based shape descriptors may not be suitable for complex shapes that consist of several disjoint regions such as trademarks or logos, emblems, clipart and characters, including various shapes in natural scenes. Region based shape descriptors, such as moments, are more reliable for shapes that have complex boundaries, because they rely not only on the contour pixels but also on all pixels constituting the shapes [1]. The Zernike Moment Descriptor is a region based shape descriptor.

The drawback of regular moments is that there is redundant information in the moments since the bases are not orthogonal and high-order moments are sensitive to noise [2]. In order to retrieve an image from a large database the descriptor should have enough discriminating power and immunity to noise. In addition, the descriptor should be invariant to scale and rotation.

The Zernike moment descriptor has such desirable properties: rotation invariance, robustness to noise, expression efficiency and fast computation for describing the various shapes of patterns [3]. With a proper normalization method, scale invariance can also be achieved [4].

There are many problems in the existing CBIR systems and are given as below:

- **More Computation Time:** Time taken to retrieve the relevant images is more in the current CBIR systems.

- **More Retrieval Time:** Images should be retrieved in a specified time but time taken to retrieve the relevant images by current CBIR systems is too much.
- **Accuracy:** In most of the CBIR systems relevant images are not retrieved on the top ranked results.

In this paper, we have overcome all these problems by making use of fast q-recursive method to calculate radial polynomials of Zernike Moments [11]. The proposed method gives best performance in terms of total retrieval time and accuracy.

The remainder of the paper is organized as follows: Section (2) focuses on literature. Section (3) emphasizes on our proposed work. In Section (4) we have discussed the results. Final Section (5) is the conclusion and future work.

2. Literature Review

Problems with traditional methods of image indexing have led to the rise of interest in techniques for retrieving images on the basis of automatically-derived features such as color, texture and shape – a technology now generally referred to as Content Based Image Retrieval.

Lu et. al [5] have used the 'linear scaling to unit variance' normalization method to equalize each dimension of the feature vector. A fast search method named equal-average K nearest neighbor search is then used to find the first K nearest neighbors of the query feature vector as soon as possible based on the squared Euclidean distortion measure. Experimental results show that the proposed retrieval method can largely speed up the retrieval process, especially for large database and high feature vector dimension [5].

A new approach to content based image retrieval by texture solved three problems: high computational time, handling high dimension data, and comparing images consistent with human perception. To decrease the computational time, a new strategy was presented to extract an image feature with high retrieval accuracy [6].

The method fast access by content is based on the image tree of contours defined for graphic images, as well as on the one dimensional complex Fourier transform of the contours. In this way, problems connected with the image normalization concerning translation, rotation, scaling, reflection and intensity are currently solved. The most informative data of the image are ordered by importance in a key of fixed length, on which the fast access is performed using the well-known index access methods of a conventional database management system (DBMS). The method is tested on a database of about 4000 images of hallmarks [7].

A novel content based image retrieval data structure is developed [8]. It can improve the searching efficiency significantly. All images are organized into a tree, in which every node is comprised of images with similar features. Images in a children node have more similarity (less variance) within themselves in relative to its parent. Upon the addition of new images, the tree structure is capable of dynamic ally changing to ensure the minimization of total variance of the tree. Subsequently, a heuristic method has been designed to retrieve the information from this tree.

Recently wavelets are used along with ZMs [9]. Dual Tree Complex Wavelets and Fourier Features are extracted for whole image database and stored separately. Afterwards query image is given and system retrieves images only on the basis of features of ZMs as it is a region based descriptor. The irrelevant images are thus filtered out and the selected database is then compared with query image on the basis of Dual Tree Complex Wavelets and Fourier Features.

A fast and robust color feature extraction method for effective content based image retrieval is used [10]. In color feature extraction, since cylindrical HSV color space is not perceptually uniform, the color quantization and similarity measure method based on a cylinder-cone transform is improved. A new rectangular approximate image segmentation is used. A significance function is also used to reflect the importance of different position in image, and improve the segmentation and retrieval performance.

3. Proposed Work

The way to increase the responding ability is to speed up the procedure of content retrieval. Fast methods of visual feature extraction can be used to make the process of content based image retrieval fast. It is hard for the traditional systems to increase the responding ability. Chong et. al [11] carry out an extensive survey of fast methods and propose a new method which is popularly known as q-recursive method, where q represents the repetition term in ZMs. The q-recursive method is reported to be the best and fastest method among all the recursive methods to compute Zernike polynomials [12].

3.1 Objectives of the proposed work:

- The main objective is to make CBIR system fast by using the fast algorithm to compute Zernike Moments. Here we take image feature (ZMs) as an index to that image and retrieve the relevant images.
- We implement the fast CBIR system which takes into consideration the low level features of image which are more comprehensive when compared to high level features.

In this paper, we use an efficient and fast algorithm for the recursive computation of Zernike polynomials. The CBIR process is made faster by using q-recursive method for fast access of contents from database of images. Fast CBIR is done in terms of:

- **Computation Time:** The computation of retrieval algorithm should not take time beyond certain prescribed limit.
- **Retrieval Time:** Images should be retrieved in a specified real time.
- **Accuracy:** Required relevant images should be retrieved on the top of the list of ranked images.

3.2 Architecture of Fast CBIR using q-recursive Method:

The architecture of fast CBIR system is shown in Figure 3.2. There are two issues in building this Fast CBIR system:

1) Every image in the image database is to be represented efficiently by extracting significant features using ZMs.
2) Relevant images are to be retrieved using similarity measure between query image and database images.

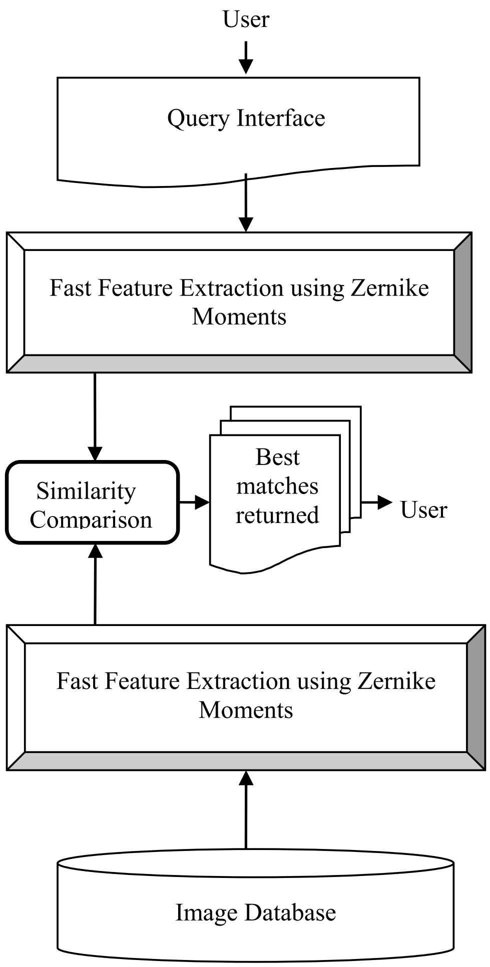

Fig 3.2: Architecture of Fast Content Based Image Retrieval System

To achieve this functionality, the fast CBIR has two main components: database population (the process of creating an image database) and a query. During the population, images are processed to extract features describing their shapes and the shape features are stored in a database. In the query phase, the user composes a query image. Features are generated from the query and then input to a matching engine that finds images from the database with similar features.

The performance of the fast CBIR system can be tested by retrieving the desired number of images from the database. The total retrieval time taken is the main performance measure in the method used for fast CBIR system. The average retrieval rate is known as the average percentage number of images belonging to the same image as the query image in the top 'N' matches. 'N' indicates the number of retrieved images.

3.3 Algorithmic Steps for Fast Content Based Image Retrieval

The q-recursive method is used to make the process of CBIR fast. The traditional approach to compute ZMs known as direct radial polynomial formulation is also implemented. It is worth mentioning that image is inscribed within a circle for computing ZMs with q-recursive method. In case of traditional ZMs, they are however computed by taking a unit disk inscribed in the image.

Steps for Content Based Image Retrieval for both q-recursive and direct method:

1. The user gives an image I as the query image.
2. a) Get the ZMs of the query image.
   b) Find the time taken to calculate ZMs of the query image.
3. Find the Mean Square Reconstruction Error (*MSRE*) for the query image.
4. a) For image ***i*** in the database obtain the ZMs.
   b) Find the time taken to calculate ZMs of the image ***i***.
5. Find the *MSRE* for image ***i*** in the database.
6. Calculate the Euclidean distance between the two sets of ZMs and store them in an array.
7. Increment ***i***. Repeat from step 4.
8. For each image ***i*** in the database, if *MSRE*<1.0 sort the array of Euclidean distances.
9. Calculate the total time taken for CBIR.
10. Retrieve the top 'N' results; N is the number of top ranked images.
11. Mark the top ranked retrieved images as relevant or irrelevant.
12. Obtain the Precision and Recall metrics for performance evaluation.

Using the above algorithm, the most relevant images are searched for in the image database. The Euclidean distance is calculated between the query image and every image of the database. This process is repeated until all the images in the database have been compared with the query image. Upon completion of the calculation of Euclidean distances, we have an array of Euclidean distances, which is then sorted. The 'N' topmost images are then displayed as a result of the search and then marked as relevant or irrelevant.

4. Results and Discussion

4.1 Dataset and Image Features

We performed our experiments over an image collection. This collection contains around 25 images associated with textual description and cataloged into 4 broad categories: butterfly, food, medical images and labels.

Image features used in our experiments are Zernike Moments. q-recursive method is used for the feature extraction using Zernike Moments. Euclidean distance function is used for the similarity measure. Figure 4.1, Figure 4.2, Figure 4.3 and Figure 4.4 show the four categories of images used as datasets.

Figure 4.1 Class 1: Butterfly Images

Figure 4.2 Class 2: Food Images

Figure 4.3 Class 3: Medical Images

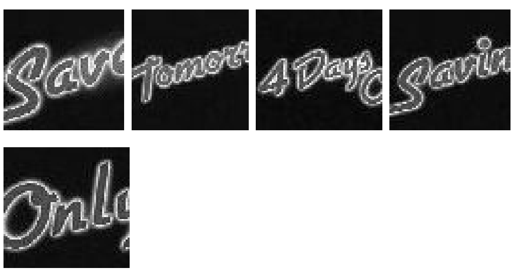

Figure 4.4 Class 4: Labels Images

4.2 Evaluation Method

The retrieval performance of any CBIR system is inherently limited by the quality of the features used to represent images. In this paper, we have performed a precision and recall study to evaluate the performance of both the methods i.e. traditional ZMs computation and fast recursive ZMs computation. This paper focuses on the ability of our relevance feedback mechanism to converge to a desired result. We run an initial query with images chosen at random from the collection and save the ranked result as the relevant list and then these results are refined.

For a given query image, mean-square reconstruction error (*MSRE*) [12] is denoted by ε_L and is calculated as:

$$\varepsilon_L = \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}\{f(x_i,y_j)-\hat{f}(x_i,y_j)\}^2}{\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f^2(x_i,y_j)} \qquad (1)$$

Here, f is the original image and $\hat{f}$ is the image reconstructed from ZMs. Euclidean Distance is measured for the images having *MSRE* less than 1.0. The system first retrieves a list of ranked images according to the Euclidean Distance as a similarity measure. Then, the user marks the retrieved images as relevant (positive examples) to the query or not relevant (negative examples). The system will refine the retrieval results based on the feedback and present a new list of images to the user.

4.2.1 Euclidean Distance

Euclidean distance is a very commonly used distance measurement. Euclidean distance actually measure dissimilarity. Small distance means small dissimilarity and large similarity. Euclidean distance is basically the sum of squared distances between two vector values and obtained by the following equation:

$$D(Q,I) = \sqrt{\sum_{i=1}^{N}(f_j^Q - f_j^I)^2} \qquad (2)$$

4.2.2 Metrics used for Performance Evaluation

Precision and recall are two widely used metrics for evaluating the correctness of a pattern recognition algorithm. For a given query q, the data set of images in the database that are relevant to the query q is denoted as $R(q)$, and the retrieval result of the query q is denoted as $Q(q)$.$Q(q)$ is the total number of both irrelevant and relevant records retrieved.

- **Recall (R):** The recall is the fraction of relevant images that is returned by the query. It is the ratio of the number of relevant records retrieved to the total number of relevant records in the database.

$$\mathrm{Re}call = \frac{R(q)}{\hat{R}(q)} \qquad (3)$$

  where $\hat{R}(q)$ is the total number of relevant records in database i.e. in the same category to which the query image belongs.

- **Precision (P):** The precision of the retrieval is defined as the fraction of the retrieved images that are indeed relevant for the query. It is the ratio of the number of relevant records retrieved to the total number of irrelevant and relevant records retrieved.

$$\mathrm{Pr}ecision = \frac{R(q)}{Q(q)} \qquad (4)$$

4.4 Experimental Study

The q-recursive method is the fastest to compute ZMs [12]. The CBIR is made fast by using the q-recursive method. The direct method to compute ZMs [13] is also implemented in CBIR. The two approaches are compared and analyzed for their accuracy, total retrieval time and numerical stability.

Table 1: Recall and precision for Class 1(Butterfly) Image Size: 64×64

Moment Order	Method used	No of relevant images	Recall and Precision Values (in %age)
5	Direct q-recursive	2 4	R=40,P=13.33 R=80,P=26.66
10	Direct q-recursive	2 4	R=40,P=13.33 R=80,P=26.66
20	Direct q-recursive	2 4	R=40,P=13.33 R=80,P=26.66
30	Direct q-recursive	2 4	R=40,P=13.33 R=80,P=26.66
35	Direct q-recursive	0 4	R=0,P=0 R=80,P=26.66

Table 2: Recall and precision for Class 2(Food) Image Size: 64×64

Moment Order	Method used	No of relevant images	Recall and Precision Values (in %age)
5	Direct q-recursive	2 3	R=50,P=13.33 R=75,P=20
10	Direct q-recursive	2 3	R=50,P=13.33 R=75,P=20
20	Direct q-recursive	1 3	R=25,P=6.66 R=75,P=20
30	Direct q-recursive	1 3	R=25,P=6.66 R=75,P=20
35	Direct q-recursive	0 3	R=0,P=0 R=75,P=20

Table 3: Recall and precision for Class 3(Medical) Image Size: 64×64

Moment Order	Method used	No of relevant images	Recall and Precision Values (in %age)
5	Direct q-recursive	0 0	R=0,P=0 R=0,P=0
10	Direct q-recursive	0 2	R=0,P=0 R=40,P=13.33
20	Direct q-recursive	0 3	R=0,P=0 R=60,P=20
30	Direct q-recursive	0 3	R=0,P=0 R=60,P=20
35	Direct q-recursive	0 3	R=0,P=0 R=60,P=20

Table 4: Recall and precision for Class 4(Labels) Image Size: 64×64

Moment Order	Method used	No of relevant images	Recall and Precision Values (in %age)
5	Direct q-recursive	3 5	R=42.85,P=20 R=71.42,P=33.33
10	Direct q-recursive	2 5	R=26.57,P=20 R=71.42,P=33.33
20	Direct q-recursive	2 5	R=26.57,P=13.33 R=71.42,P=33.33
30	Direct q-recursive	2 5	R=26.57,P=13.33 R=71.42,P=33.33
35	Direct q-recursive	0 5	R=0,P=0 R=71.42,P=33.33

Table 5: Total Retrieval Time (in seconds) Image Size: 64×64

Moment Order	Total Retrieval Time taken by Direct method (in sec)	Total Retrieval Time taken by q-recursive method (in sec)
5	8.609	0.032
10	27.969	0.126
20	109.627	0.357
30	246.173	0.735
35	-	0.888
50	-	1.639

Table 6: *MSRE*(ε_L) for Class 1 Image Size: 64×64

Moment Order	*MSRE* Direct method	*MSRE* q-recursive method
5	0.494267	0.091724
10	0.534892	0.058560
20	0.335957	0.061277
30	0.324148	0.051857
35	1.000000	0.026130
50	1.000000	0.020648

- **Numerical Stability:** The numerical stability of both the methods are analyzed in terms of Mean Square Reconstruction Error (ε_L) [12] with respect to the order of moments for a given image size. *MSRE* for an image of Class 1(Butterfly) is shown in Table 6. It shows that *MSRE* for the direct method becomes 1 for moment order 35 while for q-recursive method it keeps on decreasing with the moment order.
  It shows as the moment order increases, numerical stability of direct method becomes very poor. Numerical stability of q-recursive method increases with respect to the order of moments. So q-recursive method is more stable [12] and retrieves maximum number of relevant images.
- **Total Retrieval Time:** The total time taken by both the methods to retrieve the relevant images for CBIR is shown in Table 5. For the moment order 30 total time taken by direct method is 246.173 sec and by q-recursive is 0.735 sec. It shows that the proposed method is many times faster than the direct ZMs based CBIR. Thus the proposed method makes the CBIR system fast by retrieving maximum number of relevant images in minimum amount of time.
- **Accuracy:** Accuracy is calculated on the basis whether the retrieved images are relevant or irrelevant. It is measured in terms of Recall (R) and precision (P). Tables 1, 2, 3 and 4 show the R and P for all class (i.e. 1 to 4) images respectively. The tables show that R and P for direct method decreases with the moment order. In the case of q-recursive method either it increases with the moment order or remains constant. In Table 4, R and P for q-recursive method increases with moment order while in table 1 it remains constant. Recall value in most of the cases is more than 75%. It implies that the system retrieves the maximum number of relevant images from database using q-recursive method.

Hence, q-recursive method tends to give consistent performance whereas direct method (probably due to inherent instability) performs inconsistently and is relatively less accurate.

5. Conclusions and Future Work

5.1 Conclusions

The CBIR is made fast by using the fastest method to compute Zernike Moments. There are two approaches to compute ZMs of an image function–direct radial polynomial formulation and q-recursive method. The two approaches are compared and analyzed for their accuracy, time complexity and numerical stability. Based on the above analysis, the following conclusions are drawn.

- The q-recursive method is very fast. Time taken by q-recursive method for CBIR is lowest of all the fast methods available to retrieve the images on the basis of content.
- Direct method used for CBIR is not numerically stable, as the moment order increases, numerical stability becomes very poor. So number of relevant images retrieved becomes less and performance of CBIR degrades.
- The q-recursive method used for radial polynomial formulation of ZMs is numerically stable even for very large orders of moment. The numerical stability increases with respect to image size. Therefore, it retrieves maximum number of images that are the most relevant.

5.2 Future Work

We intend to integrate various other features i.e. color, texture with ZMs features.

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Ekta Walia received her Bachelor's degree in Computer Science from Kurukshetra University, India, in 1995 and Masters in Computer Applications as well as Ph.D. (Computer Science) from Punjabi University, Patiala, India in 1998 and 2006 respectively. After starting her professional career as a software consultant with DCM DataSystems, New Delhi, India, in 1998, she served as Lecturer and Senior Lecturer in the National Institute of Technical Teachers Training and Research (NITTTR), Chandigarh, India for 07 years, where she was primarily involved in conducting short term courses for teachers of various engineering and polytechnic colleges. She has also acted as resource person for curriculum development workshops, instruction material development and was responsible for conducting research during her service at NITTTR. From 2007 to 2009, she worked as Reader in the Department of Computer Science, Punjabi University, Patiala, India. Later she served as Professor and Head in the Department of Information Technology, M.M.University, Mullana, India from 2009 to 2011. In both these assignments she was actively involved in teaching and research, mentoring as well as infrastructural development. At present, she is serving as Associate Professor in Department of Computer Science, South Asian University, New Delhi, India. Her academic achievements include University Gold medals in Graduation as well as in Post Graduation. She has authored two textbooks. Her research interests include 3D Rendering, Digital Image Watermarking, Content Based Image Retrieval and Face Recognition.